Pak. j. life soc. Sci. (2024), 22(2): 23115-23128 E-ISSN: 2221-7630;P-ISSN: 1727-4915

Pakistan Journal of Life and Social Sciences

www.pjlss.edu.pk

https://doi.org/10.57239/PJLSS-2024-22.2.001644

RESEARCH ARTICLE

Artificial Intelligence in Organ Transplantation: A Systematic Review of Current Advances, Challenges, and Future Directions

Sooraj Kumar[1], Ashish Shiwlani[2*], Syed Umer Hasan[3], Samesh Kumar[4], Faryal Shamsi[5], Sara Hasan[6]

[1]DePaul University Chicago

[2*] Illinois Institute of Technology, Chicago, Illinois

[3]Fitchburg State University - 160 Pearl St, Fitchburg, MA 01420

[4]Georgia Institute of Technology

[5]Department of Computer Science, Sukkur IBA University Pakistan

[6]University of Sussex

ARTICLE INFO

Received: Oct 15, 2024

Accepted: Dec 14, 2024

Keywords

Artificial Intelligence in Organ Transplantation

Donor-Recipient Matching

Graft Survival Prediction

Post-Operative Care Optimization

Big Data Integration in Transplantation

***Corresponding Author:**

shiwlaniashish@gmail.com

ABSTRACT

Solid-organ transplantation is a life-saving procedure. In addition to the enormous advancements of the past few decades, new difficulties have surfaced. This systematic review reviews the current applications of artificial intelligence in organ transplantation, focusing on donor-recipient matching, graft survival prediction, and post-operative care optimization. Following the PRISMA guidelines, we analyzed 22 peer-reviewed studies published between 2014 and 2024. The findings highlight AI's significant contributions, including improving donor-recipient compatibility using machine learning algorithms, predicting graft survival through advanced modelling, and enhancing post-operative monitoring with real-time analytics. Fortunately, transplantation has access to enormous data sets that can be used to build machine learning algorithms. Despite these advancements, challenges such as data heterogeneity, model interpretability, and ethical concerns persist. Current AI systems also often need help to assimilate novel data types of genomics, proteomics, and real-time clinical monitoring into predictive frameworks. More work is needed to guarantee generalizability through extensive external validation, enhance the interpretability of these algorithms, and build the infrastructure necessary for clinical integration.

I. INTRODUCTION

Organ transplantation is one of the pillars of modern medicine, providing life-saving interventions for patients with end-stage organ failure [1]. The results of solid organ transplantation have significantly improved in the last few decades. However, there are still difficulties at different stages of the transplant process. Due to the limited supply of donor organs and the continuously rising demand, organ allocation is a significant limiting factor [2]. These challenges persist against the backdrop of increasing global demand for organ transplantation, driven by rising incidences of chronic diseases such as diabetes, cardiovascular disorders, and liver failure [3]. The gap between organ availability and demand remains a significant bottleneck, with thousands of patients succumbing annually while awaiting transplantation. Innovative strategies are urgently needed to improve organ transplantation's efficiency, fairness, and outcomes [4].

Artificial intelligence (AI), a transformative technology, has demonstrated immense potential across diverse fields of medicine, from diagnostics to precision therapy [5]. A computer program that learns from examples to produce repeatable predictions and classifications on previously unseen data is known as machine learning (ML), a subfield of artificial intelligence (AI). There are three types of machine learning: (1) supervised, which involves manually mapping an observation's characteristics to a known outcome; (2) unsupervised, which involves using unlabeled data to discover innate patterns; and (3) reinforcement learning, which involves training ML models in an interactive environment to make a series of decisions by using trial and error with continuous feedback [6], [7]. A stepwise strategy from supervised to semi-/unsupervised models, which would entail training these models directly for clinical outcomes, would be suggested by mapping the journey's shape. This typically results in improved performance in machine learning, making up for any possible interpretability issues.

AI overcomes the limits and allows for real-time assessment of vast datasets, thus offering customized and applicable insights to individual patients [10]. UNOS has lately deployed technology-enabled algorithms to target offers to centres most likely to use them more accurately. UNOS has piloted the Organ Offer Explorer tool, which compares new organ offers to the surgeon's previously accepted organs and only sends organs consistent with previous behaviours to the transplant program to improve surgeon satisfaction and reduce unwanted organ offers. With AI being a data-driven intelligence augmented by human expertise, this system may improve transplantation practices' precision, efficiency, and equity [10].

Artificial intelligence and machine learning systems are attractive in a variety of domains, including medicine, due to their capacity to continually apply learning algorithms in real-time and integrate data from many sources. The amount of data created during patient care has increased dramatically over the past 20 years due to changes in regulations and advancements in medicine [11]. Care should be taken when using psychosocially derived prediction tools to guide or improve pre-transplant selection procedures. Instead, these predictive models might be most appropriate for guiding focused post-transplant interventions, which in turn could help allocate resources for better medication adherence and alcohol relapse prevention [12]. Most studies that use AI in transplantation rely on retrospectively collected data, raising concerns about the applicability of their findings to everyday clinical practice [13]. Algorithmic bias and the interpretability of AI decisions also present challenges [12], [13].

A systematic review of the current literature is needed to bridge the gaps and outline the future course for integrating AI into routine clinical care. By synthesizing the evidence on AI applications in organ transplantation, this review aims to provide a comprehensive understanding of its current capabilities, limitations, and opportunities for future research. To increase organ discard and lower waitlist mortality, machine learning has been used to optimize donor selection in order to identify patients who are likely to benefit from transplanting higher-risk organs. At the same time, it highlights the challenges impeding the clinical adoption of AI, including data quality issues, ethical dilemmas, and the need for robust validation and regulatory oversight. Throughout the transplant process, management solutions powered by AI and technology are now accessible.

II. Objectives

Three key objectives of this systematic review are:

- To evaluate the current state of AI applications in organ transplantation

- Explore future research and innovation opportunities, especially in integrating novel data types such as genomics, proteomics, and real-time clinical monitoring in AI models.
- Identify the barriers to adopting AI in transplantation, including technical, ethical, and regulatory challenges.

III. METHODOLOGY

The preparation of this research was conducted by following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) statement for reporting systematic review studies as conducted by [55,56]. This study consisted of three stages:

i. Database Selection

The data for this study were obtained from the PubMed and Web of Science (WOS) databases. The leading database of biomedical literature, PubMed, was utilized in this study to access a variety of peer-reviewed research. The most comprehensive and oldest citation index collections, WOS, were consulted, along with more than 10,000 key scholarly pieces. It covered a diverse range of fields, such as the natural sciences, biomedicine, engineering technology, and the humanities, which would be ideal to consult for interdisciplinary topics such as artificial intelligence in organ transplantation.

ii. Search Strategy

A search strategy was developed to find peer-reviewed articles on the topic "Artificial Intelligence in Organ Transplantation: Current Applications, Challenges, and Opportunities," as shown in Figure 1. The MESH terms and keywords used in this search included the following: "organ transplantation" OR "solid organ transplant" OR "transplantation" AND "artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" AND "predictive models" OR "clinical decision support" OR "donor-recipient matching." The search was run on 20th September 2024, and the article publication date range was last ten years (2014–2024).

Figure 1: Strategy for article screening and inclusion

iii. Articles Screening

Based on these keywords, 150 publications were found across the two databases. On deduplication, 67 articles were removed, leading to 83 unique studies. The remaining studies were further screened based on the inclusion and exclusion criteria as outlined in Table I [57,58]. After reviewing titles and abstracts to ensure alignment with the research objectives, 25 articles were selected. A full-text analysis of these articles was conducted, and after this, 22 studies were finally included in the review as most relevant to the research questions and scope.

Table I: Inclusion and Exclusion Criteria

Inclusion Standards	Exclusion Standards
Studies focused on AI applications in organ transplantation	Studies unrelated to organ transplantation or AI
Studies including quantitative analysis and peer-reviewed	Literature reviews or non-peer-reviewed articles
Studies published within the last 10 years (2014–2024)	Studies published before 2014
Research addressing donor-recipient matching, post-transplant care, or predictive modeling	General AI studies with no focus on transplantation

IV. Research Findings:

The review summarized the following points:

A. Evaluation of the current state of AI applications in organ transplantation

Artificial intelligence applications in organ transplantation are found to be transformative in addressing significant challenges related to donor-recipient matching, graft survival prediction, and optimization of postoperative care [7]. Findings from this systematic review outline significant progress, limitations, and opportunities in applying AI in the transplantation process [8]. This section reports on the current state of AI applications under the following themes: donor-recipient matching, graft survival prediction, and postoperative care optimization [10].

i. AI in Donor Recipient Matching

Donor-recipient matching is a vital aspect of organ transplant that calls for an intensive analysis of compatibility factors to ensure desired outcomes. In the future, AI-enabled models will probably help speed up the evaluation of liver organ quality. AI has transformed the entire gamut with its data-driven predictive models in this space [13]. Promptly identifying these patients and their referral to Organ Procurement Organizations (OPOs) is the only way to identify potential organ donors. ML may make it possible to identify potential organ donors more effectively. Choosing a donor is a challenging and complex process impacted by match considerations, donor and recipient circumstances, and more. To more accurately evaluate the interplay between donor and recipient characteristics and their overall influence on post-transplant outcomes, risk models have been applied to heart, kidney, and liver transplantation. Consequently, machine learning and discrete optimization have been applied in the context of paired kidney exchange. Machine learning technologies have been utilized to integrate certain donor traits with receiver ones to create matches with the highest post-transplant survival. AI algorithms trained in large donor and recipient profile datasets have shown potential in accurately predicting better compatibility. For example, ML algorithms have been used to develop predictions of the risk of immune rejection based on HLA disparities [14]. AI has enabled the development of predictive scoring models that pool together various donor-recipient parameters like age, comorbidities, organ quality, and immunological profiles [15], [16].

ii. AI in Graft Survival Prediction

Tissue histopathology evaluation has traditionally been used to diagnose graft rejection. However, inadequate repeatability and inter-observer variability typically limit the assessment of transplant biopsies. Machine learning (ML) has been used to produce more conclusive, standardizable methodologies to reduce the variability in the interpretation of biopsy data. Heart transplant recipients' endomyocardial samples have been subjected to supervised learning techniques to predict rejection through microarray analysis. Predicting graft survival is critical for long-term transplantation success. AI models have demonstrated remarkable capabilities in identifying factors influencing graft longevity and predicting outcomes more precisely than traditional statistical methods. One key application of AI models in identifying graft failure risk factors has been based on complex dataset analysis [18]. An instance includes the application of deep learning algorithms to analyze histopathological images for the early detection of graft rejection [19]. Applications of survival analysis models in machine learning approaches are used to predict the time of graft failure. The approach employs clinical, genetic, and environmental variables to estimate the survival probabilities [20]. Because machine learning (ML) models can integrate more factors and data kinds, they can predict short- and long-term patient survival after transplantation more accurately than advanced biostatistical models using pre-transplant characteristics of donors and recipients.

iii. Real-Time Monitoring and Prognosis

AI-driven systems have also enabled real-time monitoring of graft health. Since organs must be recovered as quickly as possible to guarantee the best potential outcome for the recipient, timing is crucial in the transplant procurement process. In addition to all of this, evaluating a donor frequently presents challenges, and the results of these evaluations are crucial when considering the potential recovery of organs that would have been mistakenly discarded or, on the other hand, the potentially appropriate disposal of donors with unacceptable risk profiles. Wearable sensors combined with AI algorithms analyze physiological parameters to provide early warnings of potential complications. As a pilot study on kidney transplant recipients reported, this approach reduces reliance on invasive procedures and facilitates timely interventions [21]. Effective postoperative care will prevent complications, improve patient quality of life, and ensure graft longevity. Predicting patient survival both on the waiting list and following a transplant is essential for optimal decision-making and care, which aims to enhance overall results and increase the number of successful transplants. Deep learning methods have created several survival models before and after transplantation. AI models have been used to tailor immunosuppressive therapy to patient-specific factors, including pharmacogenomic profiles and immune response data. Personalized regimens reduce the risk of over- or under-immunosuppression, thereby reducing complications such as infection or chronic rejection [21]. The sole method to find possible organ donors is to quickly identify these patients and refer them to Organ Procurement Organizations (OPOs). ML might enable more efficient identification of possible organ donors. Selecting a donor is challenging and intricate, influenced by several factors, including recipient and donor conditions and match concerns. Risk models have been used to more precisely assess how donor and recipient variables interact and how they collectively affect post-transplant outcomes.

iv. Early Detection of Postoperative Complications

Recipients need rigorous monitoring for a certain amount of time after transplantation, and then they need to have regular testing for the rest of their lives. Every transplant hospital has the problems of managing immunosuppression, keeping regular follow-ups, and trying to detect post-operative issues early. Complications, including infection, acute graft rejection, and delayed graft function, are major concerns in the early post-operative phase. Infection and vascular thrombosis following postoperative complications are significant causes of graft failure. AI models have recently emerged that utilize electronic health records and predictive analytics to predict complications before they arise [22]. The integration of AI with telemedicine has enabled remote monitoring of transplant recipients. AI-based platforms analyze data from wearable devices and provide real-time feedback to healthcare providers. This approach increases patient engagement and decreases hospital readmissions [23].

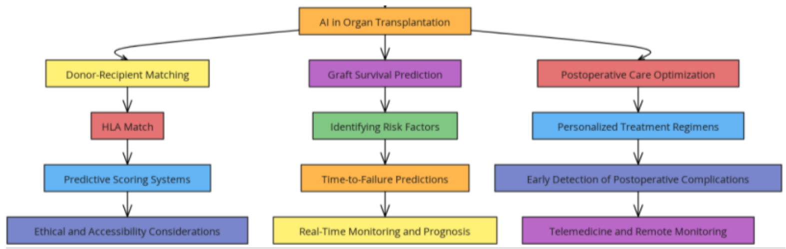

Figure 2. Summary of AI contributions to organ transplantation

B. Integration of Big Data in Future AI Applications in Organ Transplantation

AI offers the transformative potential of integrating different and innovative data types, such as genomics, proteomics, and real-time clinical monitoring of AI models in organ transplantation.

i. Genomics and Proteomics in AI Models

Genomic data offers an overview of genetic variations influencing the immune response. Integrating whole-genome or targeted sequencing data into AI models predicts the probability of rejection and thus tailors immunosuppressive therapy [24]. For instance, SNPs related to graft tolerance could improve the accuracy of donor-recipient matching by utilizing genomic biomarkers [25].

Proteomics, a large-scale protein science, provides insights into dynamic cellular and tissue processes [25]. For example, AI-powered proteomic analysis can identify early biomarkers for graft dysfunction, such as changes in protein expression related to rejection or ischemia-reperfusion injury [26]. Such a data set would lead to predictive models that detect complications before clinical symptoms appear [27].

ii. Multi-Modal Data Integration

Integrating genomics, proteomics, imaging, and clinical data into unified AI frameworks can provide a holistic understanding of transplant dynamics [28]. Multi-modal AI models can leverage these data sources to improve predictive accuracy, identify complex patterns, and deliver personalized recommendations. Despite its promise, integrating multi-modal data poses challenges such as harmonization, storage, and processing. The emergence of federated learning and cloud-based platforms are potential solutions. Future research should also focus on developing interpretable models that clinicians can trust and quickly adopt in their workflows [29].

TABLE 2. Summary of Studies Using Machine Learning for Predicting Patient Survival or Graft Outcomes Post-Transplantation

Ref	Prediction	Data	ML Model Used	Result
[35]	Survival post-heart Tx (1 y)	UNOS Registry, 1987–2014 (n = 56,477)	ANN, SVM, tree-based models	ANN performed best with a C-statistic = 0.66, regression at 0.65
[36]	Survival post-heart Tx & waiting list mortality	UNOS Registry, 1985–2015 (n = 59,820, heart transplant recipients) & (n = 35,455, waiting list)	Tree-based model	Best prediction for 3-month survival: AUC = 0.66, C-statistic = 0.57; Outperformed DRI and others
[37]	Survival post-heart Tx (9 y)	UNOS, 1987–2012 (n = 13,720)	Bayesian Belief Network	BBN method showed comparable predictive performance to other leading approaches
[38]	Survival post-heart Tx (1 y)	ISHLT registry, 1994–2010 (n = 56,625), validation (n = 1,285)	ANN, tree-based models	IHSTA outperformed other models (AUROC: IHSTA = 0.65, RSS = 0.61, IMPACT = 0.61, DRI = 0.56)
[39]	Outcomes post-heart-lung Tx	UNOS Registry (1987–2009) (n = 16,604)	ANN, tree-based models	Identified novel features that improved CoxPH models' performance
[40]	Survival following lung Tx	UNOS Registry, 1987–2010 (n = 106,394)	ANN, SVM, tree-based models	SVM identified optimal features (R^2 = 0.879) for survival prediction
[41]	Survival post-heart Tx (1 y)	UNOS Registry, 1997–2011 (n = 27,860)	IHSTA, IMPACT models	1-year survival: AUROC for IHSTA = 0.654, IMPACT = 0.608
[42]	Survival post-heart Tx (pediatric)	UNOS Registry, 2006–2015 (n = 3,502)	ANN, tree-based models	1-year survival: AUROC for RF = 0.72, ANN = 0.65, CART = 0.67
[43]	Mortality post-liver Tx	Patient data, Iran, 2008–2013 (n = 1,168)	Artificial neural network	AUROC: 86.4% (ANN), 80.7% (CoxPH)
[44]	Mortality post-liver Tx (90 d)	UNOS Registry, 2002–2013 (n = 30,458)	ANN, tree-based models	AUROC: 0.61 (all patients), 0.952 (≥10% predicted mortality)
[45]	3-mo mortality and organ allocation	Multicenter study, Spain, 2007–2008 (n = 1,003)	Artificial neural network	Developed a rule-based system for donor allocation
[46]	30-d graft failure post-liver Tx	Australian Hospital, 2010–2013 (n = 180)	ANN, tree-based models	Tree-based AUROC = 0.818, ANN AUROC = 0.835, outperforming SOFT, MELD, and DRI

[47]	Graft survival (kidney)	US Renal Data System, 1990–1999 (n = 92,844)	Tree-based models	AUROC (1-, 3-, 5-, 7-, and 10-year): 0.63–0.90
[48]	Graft survival at 5 y	Patient data, Italy (n = 194)	Tree-based model	Sensitivity: 88%, specificity: 73%
[49]	Graft survival (kidney)	Patient records, Egypt, 1976–2007, live donor recipients	Regression, tree-based models	Correlation coefficients: 0.87 (rule-based), 0.737 (TBM), 0.733 (regression)
[50]	Graft rejection (kidney)	Patient records, UK, 2003–2012 (n = 80), HLA-incompatible patients	Tree-based model	85% accuracy, identified factors associated with rejection
[19]	Graft survival (kidney)	UNOS, 2004–2015 (n = 31,207)	SVM, ANN, tree-based models, BBN	Best accuracy with BBN: 68.4% for fused data mining models
[51]	Graft survival (kidney)	Patient records, Iran, 2002–2007 (n = 717)	SVM, ANN, Logistic Regression	AUROC: SVM = 0.86, ANN = 0.769, LR = 0.774
[52]	Graft survival (kidney)	Multicenter Study, Korea, 1997–2012 (n = 3,117)	Tree-based models	Survival decision tree model: Best performance (C-Index 0.80) for 10-year survival
[53]	Graft survival (kidney)	UNOS, 2002–2011 (n = 163,199)	Tree-based model	5-year C-Index = 0.724, outperformed the EPTS score
[54]	Graft survival (kidney)	Patient data, Iran, 2007–2013 (n = 513)	ANN, tree-based models	ANN: 83.7%, tree-based models: 83.28%–87.21%

V. Challenges and Future Directions

Integrating big data into AI models for organ transplantation is fraught with several challenges. One of the major hurdles is the issue of heterogeneity. Genomic, proteomic, and clinical data are generated from different sources with formats, scales, and measurement standards. This makes data preprocessing, alignment, and harmonization time-consuming and computationally intensive [25]. For example, the sheer volume of data from high-throughput genomic and proteomic technologies forms significant storage and processing challenges. Traditional computational infrastructure often breaks down and requires special cloud-based or high-performance computing system arrangements [26].

Another critical challenge is the quality and completeness of data [29]. Clinical datasets, especially those retrospectively obtained, often contain errors or are partially incomplete, which usually degrades performance on AI models [30]. Moreover, biases in the data resulting from an overabundance of demographic or clinical groups can result in models that need to be more generalized across diverse populations [31]. Such biases can widen healthcare inequalities in access and outcomes [30].

Ethical and regulatory hurdles are also significant. Such uses of sensitive genomic and clinical information pose concerns about patient privacy and safety in data security [32]. Compliance with strict regulations, such as HIPAA or GDPR, is difficult for such purposes, particularly when multiple stakeholders or international collaborations are involved. Further, ethical issues concerning consent for using personal health data in AI development must be addressed to maintain patients' trust and adhere to ethical research practices [33].

Despite the developments, AI models incorporating big data into organ transplantation face significant limitations [34]. The main limitation is that many AI algorithms, intense learning models, remain a "black box." While they may be highly accurate, the models must be more interpretable and help clinicians understand the reasoning behind the predictions [34]. Lack of transparency does not instill trust and acceptance among healthcare providers who are afraid to adopt something they need help understanding [34].

Another area for improvement is the poor representation of some patient subgroups in the training datasets used for AI model development [35]. Patients from underrepresented ethnicities or rare clinical conditions need to be better represented, leading to biased predictions that fail to account for unique genetic or clinical traits [35]. This may lead to recommendations for AI that could be more effective and beneficial for specific populations.

Most importantly, current AI models face challenges in using longitudinal data correctly. Organ transplantation is a time-variant process as a patient's state changes over time; hence, models must continuously learn this time variant. Several AI models trained in a static dataset fail to capture any temporal changes, thus limiting their usage in a practical clinical setup [34].

Finally, while multimodal data integration holds great promise, it remains in its infancy [36]. Most AI models today are designed to handle singular data types, such as imaging or genomic sequences. The technical challenge in integrating diverse data types is the difference in structure, scale, and relevance, making it challenging to maintain a unified framework. This currently limits the development of genuinely inclusive models that could revolutionize personalized medicine in transplantation [20].

The future of AI in organ transplantation is built around the challenges and limitations, innovative solutions, and research directions [6]. One promising direction is the development of Explainable AI (XAI) models. These models seek to make AI predictions more interpretable, provide insights into decision-making, and increase clinicians' trust. XAI tools can enable healthcare providers to validate AI recommendations against their expertise and foster collaboration between humans and machines [6], [33].

A more significant focus area is the generation of standard, high-quality datasets. Coordinated efforts by hospitals, research institutions, and technology companies may result in large, anonymized databases encompassing patients from various backgrounds [8], [34]. These datasets will improve the quality of model training, eliminate some biases, and increase generalizability. Federated learning, a technique that allows models to learn from distributed datasets without centralizing data, could further ease data sharing while ensuring privacy [33].

Technology and artificial intelligence are growing in importance as healthcare decision-making aids. The increasing volume of easily accessible patient data and the widespread availability of technology support the quick integration of big data analytics into transplant care. Without a trustworthy evaluation of the expected results given a particular donor and their features, centre-specific algorithms have greatly impacted clinical decision-making at various stages of transplant care to direct donor organ selection and recipient approval.

Further, real-time data streams from wearable and implantable devices may revolutionize post-operative care. AI systems that analyze the data streams in real time would provide early warnings of complications or advice to modify treatment plans. More access and patient engagement benefit, especially when integrated with telemedicine platforms in resource-limited settings [28].

Finally, addressing ethical and regulatory challenges is crucial for the widespread adoption of AI in organ transplantation [32]. Future research should focus on developing robust frameworks for data governance, emphasizing transparency, security, and equitable access. Engaging stakeholders - patients, clinicians, and policymakers - in developing and deploying AI systems will be essential for ensuring ethical and sustainable innovations [33].

By addressing these challenges and exploring directions, AI can significantly advance the field of organ transplantation, improving outcomes and quality of life for patients worldwide.

VI. CONCLUSION

This systematic review underlines AI's transformative role in organ transplantation, from enhancing donor-recipient matching to improving comes at late stages after graft implantation. Although AI has shown immense potential, its usage is presently limited by data quality and integration, hurdles, and ethical considerations. Development of standardized datasets of the highest quality and AI models explained in multi-modality need collaborative efforts. Integrating novel data types such as genomics, proteomics, and real-time monitoring can enhance predictive accuracy and personalized care. Overcoming these barriers will drive innovation in organ transplantation, improving patient survival and quality of life while setting a benchmark for the future of precision medicine.

VII. REFERENCES

1. Black, C. K., Termanini, K. M., Aguirre, O., Hawksworth, J. S., & Sosin, M. (2018). Solid organ transplantation in the 21st century. *Annals of translational medicine*, *6*(20).
2. Rana, A., Gruessner, A., Agopian, V. G., Khalpey, Z., Riaz, I. B., Kaplan, B., ... & Gruessner, R. W. (2015). Survival benefit of solid-organ transplant in the United States. *JAMA surgery*, *150*(3), 252-259.

3. Massie, A. B., Kuricka, L. M., & Segev, D. L. (2014). Big data in organ transplantation: registries and administrative claims. *American Journal of Transplantation*, *14*(8), 1723-1730.
4. Dew, M. A., Rosenberger, E. M., Myaskovsky, L., DiMartini, A. F., Dabbs, A. J. D., Posluszny, D. M., ... & Greenhouse, J. B. (2016). Depression and anxiety as risk factors for morbidity and mortality after organ transplantation: a systematic review and meta-analysis. *Transplantation*, *100*(5), 988-1003.
5. Hirani, N., & Chatterjee, P. (2024). A systematic review on Artificial Intelligence applied to predictive cardiovascular risk analysis in liver transplantation. *F1000Research*, *13*(701), 701.
6. Thongprayoon, C., Hansrivijit, P., Leeaphorn, N., Acharya, P., Torres-Ortiz, A., Kaewput, W., ... & Cheungpasitporn, W. (2020). Recent advances and clinical outcomes of kidney transplantation. *Journal of Clinical Medicine*, *9*(4), 1193.
7. Peloso, A., Moeckli, B., Delaune, V., Oldani, G., Andres, A., & Compagnon, P. (2022). Artificial intelligence: present and future potential for solid organ transplantation. *Transplant International*, *35*, 10640.
8. Connor, K. L., O'Sullivan, E. D., Marson, L. P., Wigmore, S. J., & Harrison, E. M. (2021). The future role of machine learning in clinical transplantation. *Transplantation*, *105*(4), 723-735.
9. National Research Council. (2022). *Realizing the promise of equity in the organ transplantation system*.
10. Gotlieb, N., Azhie, A., Sharma, D., Spann, A., Suo, N. J., Tran, J., ... & Bhat, M. (2022). The promise of machine learning applications in solid organ transplantation. *NPJ digital medicine*, *5*(1), 89.
11. Rahman, M. A., Yilmaz, I., Albadri, S. T., Salem, F. E., Dangott, B. J., Taner, C. B., ... & Akkus, Z. (2023). Artificial intelligence advances in transplant pathology. *Bioengineering*, *10*(9), 1041.
12. Naimimohasses, S., Keshavjee, S., Wang, B., Brudno, M., Sidhu, A., & Bhat, M. (2024). Proceedings of the 2024 Transplant AI Symposium. *Frontiers in Transplantation*, *3*, 1399324.
13. Peloso, A., Naesens, M., & Thaunat, O. (2023). The Dawn of a New Era in Kidney Transplantation: Promises and Limitations of Artificial Intelligence for Precision Diagnostics. *Transplant International*, *36*, 12010.
14. Sidhom, J. W., Pardoll, D., & Baras, A. (2018). AI-MHC: an allele-integrated deep learning framework for improving Class I & Class II HLA-binding predictions. *BioRxiv*, 318881.
15. Hu, J. X., Zhao, C. F., Wang, S. L., Tu, X. Y., Huang, W. B., Chen, J. N., ... & Chen, C. R. (2023). Acute pancreatitis: A review of diagnosis, severity prediction and prognosis assessment from imaging technology, scoring system and artificial intelligence. *World Journal of Gastroenterology*, *29*(37), 5268.
16. Jammalamadaka, K. R., & Itapu, S. (2023). Responsible AI in automated credit scoring systems. *AI and Ethics*, *3*(2), 485-495.
17. Ercikan, K., & McCaffrey, D. F. (2022). Optimizing implementation of artificial-intelligence-based automated scoring: An evidence centered design approach for designing assessments for AI-based scoring. *Journal of Educational Measurement*, *59*(3), 272-287.
18. Wingfield, L. R., Ceresa, C., Thorogood, S., Fleuriot, J., & Knight, S. (2020). Using artificial intelligence for predicting survival of individual grafts in liver transplantation: a systematic review. *Liver transplantation*, *26*(7), 922-934.

19. Topuz, K., Zengul, F. D., Dag, A., Almehmi, A., & Yildirim, M. B. (2018). Predicting graft survival among kidney transplant recipients: A Bayesian decision support model. *Decision Support Systems*, *106*, 97-109.
20. Luck, M., Sylvain, T., Cardinal, H., Lodi, A., & Bengio, Y. (2017). Deep learning for patient-specific kidney graft survival analysis. *arXiv preprint arXiv:1705.10245*.
21. Narayan, R. R., Abadilla, N., Yang, L., Chen, S. B., Klinkachorn, M., Eddington, H. S., ... & Melcher, M. L. (2022). Artificial intelligence for prediction of donor liver allograft steatosis and early post-transplantation graft failure. *HPB*, *24*(5), 764-771.
22. Lau, L., Kankanige, Y., Rubinstein, B., Jones, R., Christophi, C., Muralidharan, V., & Bailey, J. (2017). Machine-learning algorithms predict graft failure after liver transplantation. *Transplantation*, *101*(4), e125-e132.
23. Kantidakis, G., Putter, H., Lancia, C., Boer, J. D., Braat, A. E., & Fiocco, M. (2020). Survival prediction models since liver transplantation-comparisons between Cox models and machine learning techniques. *BMC medical research methodology*, *20*, 1-14.
24. Bontha, S. V., Maluf, D. G., Mueller, T. F., & Mas, V. R. (2017). Systems biology in kidney transplantation: the application of multi-omics to a complex model. *American Journal of Transplantation*, *17*(1), 11-21.
25. Farkona, S., Pastrello, C., & Konvalinka, A. (2023). Proteomics: its promise and pitfalls in shaping precision medicine in solid organ transplantation. *Transplantation*, *107*(10), 2126-2142.
26. Liu, Y., Feng, R., Chen, J., Yan, H., & Liu, X. (2024). The future of organ transplantation donor selection: opportunities and challenges in the era of precision medicine. *International Journal of Surgery*, 10-1097.
27. Ramalhete, L. M., Araújo, R., Ferreira, A., & Calado, C. R. (2022). Proteomics for biomarker discovery for diagnosis and prognosis of kidney transplantation rejection. *Proteomes*, *10*(3), 24.
28. Avramidou, E., Psatha, K., St John, K., Tsoulfas, G., & Aivaliotis, M. (2025). Future of non-invasive graft evaluation: A systematic review of proteomics in kidney transplantation. *World Journal of Transplantation*, *15*(1).
29. Connor, K. L., O'Sullivan, E. D., Marson, L. P., Wigmore, S. J., & Harrison, E. M. (2021). The future role of machine learning in clinical transplantation. *Transplantation*, *105*(4), 723-735.
30. Grobe, N., Scheiber, J., Zhang, H., Garbe, C., & Wang, X. (2023). Omics and Artificial Intelligence in Kidney Diseases. *Advances in Kidney Disease and Health*, *30*(1), 47-52.
31. Burlacu, A., Iftene, A., Jugrin, D., Popa, I. V., Lupu, P. M., Vlad, C., & Covic, A. (2020). Using artificial intelligence resources in dialysis and kidney transplant patients: a literature review. *BioMed research international*, *2020*(1), 9867872.
32. Shiwlani, A., Khan, M., Sherani, A. M. K., & Qayyum, M. U. (2023). Synergies of AI and Smart Technology: Revolutionizing Cancer Medicine, Vaccine Development, and Patient Care. *International Journal of Social, Humanities and Life Sciences*, *1*(1), 10-18.
33. Khan, M., Shiwlani, A., Qayyum, M. U., Sherani, A. M. K., & Hussain, H. K. (2024). AI-powered healthcare revolution: an extensive examination of innovative methods in cancer treatment. *BULLET: Jurnal Multidisiplin Ilmu*, *3*(1), 87-98.
34. Shiwlani, A., Khan, M., Sherani, A. M. K., Qayyum, M. U., & Hussain, H. K. (2024). REVOLUTIONIZING HEALTHCARE: THE IMPACT OF ARTIFICIAL INTELLIGENCE ON

PATIENT CARE, DIAGNOSIS, AND TREATMENT. *JURIHUM: Jurnal Inovasi dan Humaniora*, *1*(5), 779-790.
35. Thatoi, P., Choudhary, R., Shiwlani, A., Qureshi, H. A., & Kumar, S. (2023). Natural Language Processing (NLP) in the Extraction of Clinical Information from Electronic Health Records (EHRs) for Cancer Prognosis. *International Journal*, *10*(4), 2676-2694.
36. Umar, M., Shiwlani, A., Saeed, F., Ahmad, A., Ali, M. H., & Shah, A. T. (2023). Role of Deep Learning in Diagnosis, Treatment, and Prognosis of Oncological Conditions. *International Journal*, *10*(5), 1059-1071.
37. Ahmad, A., Dharejo, N., Saeed, F., Shiwlani, A., Tahir, A., & Umar, M. (2024). Prediction of Fetal Brain and Heart Abnormalties using Artificial Intelligence Algorithms: A Review. *American Journal of Biomedical Science & Research*, *22*(3), 456-466.
38. Qayyum, M. U., Sherani, A. M. K., Khan, M., Shiwlani, A., & Hussain, H. K. (2024). Using AI in Healthcare to Manage Vaccines Effectively. *JURIHUM: Jurnal Inovasi dan Humaniora*, *1*(6), 841-854.
39. Husnain, A., Shiwlani, A., Gondal, M. N., Ahmad, A., & Saeed, A. (2024). Utilizing machine learning for proactive detection of cardiovascular risks: A data-driven approach. *International Journal of Science and Research Archive*, *13*(1), 1280-1290.
40. Delen, D., Oztekin, A., & Kong, Z. J. (2010). A machine learning-based approach to prognostic analysis of thoracic transplantations. *Artificial intelligence in medicine*, *49*(1), 33-42.
41. Medved, D., Ohlsson, M., Höglund, P., Andersson, B., Nugues, P., & Nilsson, J. (2018). Improving prediction of heart transplantation outcome using deep learning techniques. *Scientific reports*, *8*(1), 3613.
42. Miller, P. E., Pawar, S., Vaccaro, B., McCullough, M., Rao, P., Ghosh, R., ... & Ahmad, T. (2019). Predictive abilities of machine learning techniques may be limited by dataset characteristics: insights from the UNOS database. *Journal of cardiac failure*, *25*(6), 479-483.
43. Khosravi, B., Pourahmad, S., Bahreini, A., Nikeghbalian, S., & Mehrdad, G. (2015). Five years survival of patients after liver transplantation and its effective factors by neural network and cox poroportional hazard regression models. *Hepatitis monthly*, *15*(9).
44. Molinari, M., Ayloo, S., Tsung, A., Jorgensen, D., Tevar, A., Rahman, S. H., & Jonassaint, N. (2019). Prediction of perioperative mortality of cadaveric liver transplant recipients during their evaluations. *Transplantation*, *103*(10), e297-e307.
45. Cruz-Ramirez, M., Hervas-Martinez, C., Fernandez, J. C., Briceno, J., & De La Mata, M. (2013). Predicting patient survival after liver transplantation using evolutionary multi-objective artificial neural networks. *Artificial intelligence in medicine*, *58*(1), 37-49.
46. Lau, L., Kankanige, Y., Rubinstein, B., Jones, R., Christophi, C., Muralidharan, V., & Bailey, J. (2017). Machine-learning algorithms predict graft failure after liver transplantation. *Transplantation*, *101*(4), e125-e132.
47. Krikov, S., Khan, A., Baird, B. C., Barenbaum, L. L., Leviatov, A., Koford, J. K., & Goldfarb-Rumyantzev, A. S. (2007). Predicting kidney transplant survival using tree-based modeling. *Asaio Journal*, *53*(5), 592-600.
48. Greco, R., Papalia, T., Lofaro, D., Maestripieri, S., Mancuso, D., & Bonofiglio, R. (2010, May). Decisional trees in renal transplant follow-up. In *Transplantation proceedings* (Vol. 42, No. 4, pp. 1134-1136). Elsevier.

49. Fouad, M., Ellatif, M. M. A., Hagag, M., & Akl, A. (2015). Prediction of long term living donor kidney graft outcome: Comparison between rule based decision tree and linear regression. *Int J Adv Comp Res*, *3*, 185-92.
50. Shaikhina, T., Lowe, D., Daga, S., Briggs, D., Higgins, R., & Khovanova, N. (2019). Decision tree and random forest models for outcome prediction in antibody incompatible kidney transplantation. *Biomedical Signal Processing and Control*, *52*, 456-462.
51. Nematollahi, M., Akbari, R., Nikeghbalian, S., & Salehnasab, C. (2017). Classification models to predict survival of kidney transplant recipients using two intelligent techniques of data mining and logistic regression. *International journal of organ transplantation medicine*, *8*(2), 119.
52. Yoo, K. D., Noh, J., Lee, H., Kim, D. K., Lim, C. S., Kim, Y. H., ... & Kim, Y. S. (2017). A machine learning approach using survival statistics to predict graft survival in kidney transplant recipients: a multicenter cohort study. *Scientific reports*, *7*(1), 1-12.
53. Mark, E., Goldsman, D., Gurbaxani, B., Keskinocak, P., & Sokol, J. (2019). Using machine learning and an ensemble of methods to predict kidney transplant survival. *PloS one*, *14*(1), e0209068.
54. Ordu, M., Demir, E., Tofallis, C., & Gunal, M. M. (2021). A novel healthcare resource allocation decision support tool: A forecasting-simulation-optimization approach. *Journal of the operational research society*, *72*(3), 485-500.
55. Nasrullah Dharejo, Mumtaz Aini Alivi, Muhammad Saleeh Rahamad, Xu Jiaqing, & Maria Brony. (2023). Effects of Social Media Use on Adolescent Psychological Well-Being: A Systematic Literature Review. *International Journal of Interactive Mobile Technologies (iJIM)*, *17*(20), pp. 171–191. https://doi.org/10.3991/ijim.v17i20.44663
56. Xu Jiaqing, Mumtaz Aini Alivi, Siti Ezaleila Mustafa, & Nasrullah Dharejo. (2023). The Impact of Social Media on Women's Body Image Perception: A Meta-Analysis of Well-being Outcomes. *International Journal of Interactive Mobile Technologies (iJIM)*, *17*(20), pp. 148–170. https://doi.org/10.3991/ijim.v17i20.44665
57. Jun, G., Xu, J., Alivi, M. A., Zhewen, F., Dharejo, N., & Brony, M. (2025). Impacts of digital media on children's well-being: A bibliometric analysis. *Online Journal of Communication and Media Technologies* , *15* (1), e202501.
58. Brony, M., Alivi, M.A., Syed, M.A.M., & Dharejo, N. (2024). A Systematic Review on Social Media Health Communications and Behavioral Development among Indians in the COVID-19 Context. *Studies in Media and Communication* , *12* (2), 37-49.